Module 4

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Activity 1

Three classification algorithms were implemented and compared:

1. Least Squares for Classification
2. Fisher Linear Discriminant
3. Perceptron

The data set consists of two classes with Gaussian PDF, where the mean and covariance matrices were deduced from Figure 4.6 in Bishop, assuming the 1σ contour. The classes have considerable overlap in the projected space.

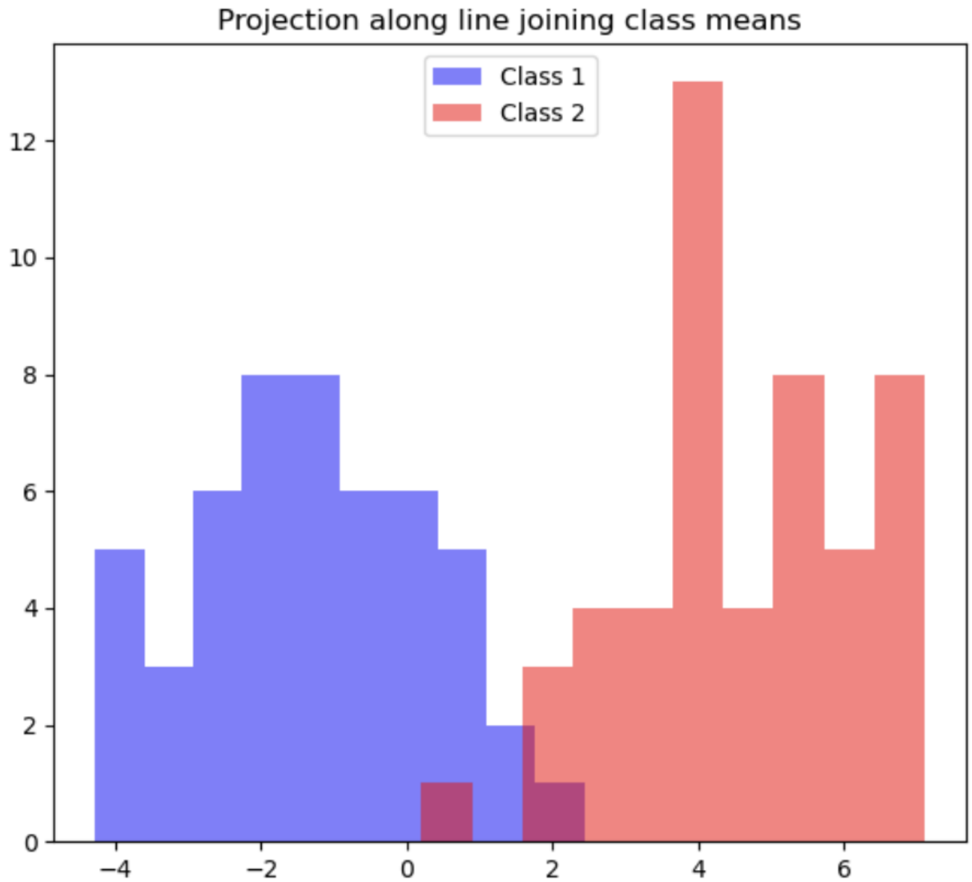

Figure 1: Visualization of the dataset showing the two classes and their means.

Least Squares Classification

The least squares classification method fits a linear model to minimize the sum of squared errors between the predicted output and the target values.

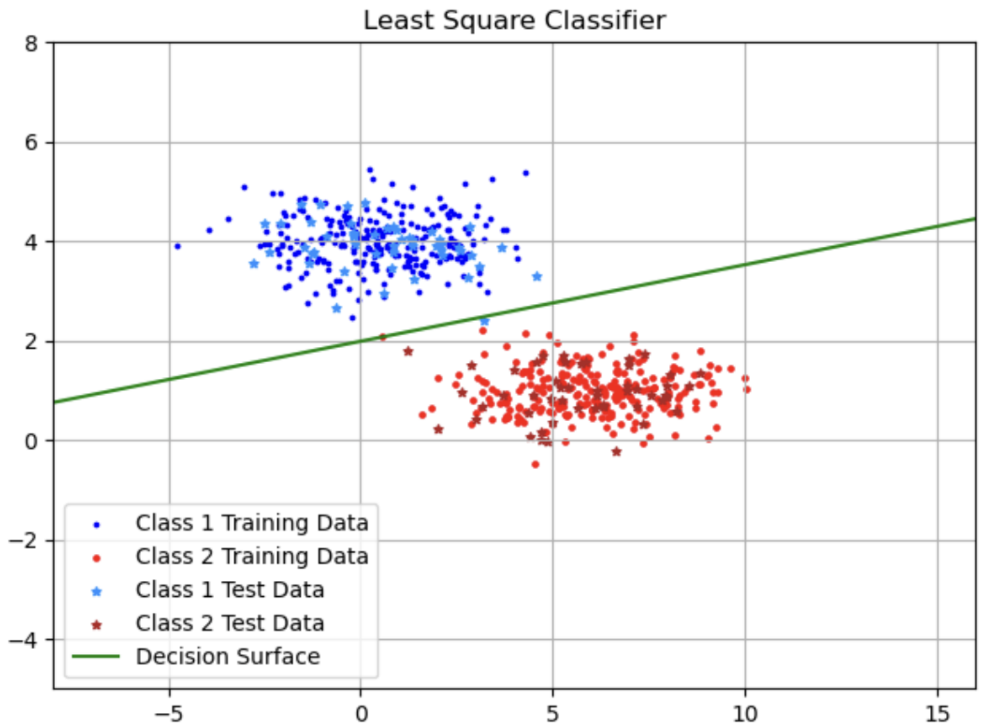

Figure 2: Decision boundary for Least Squares classification.

The confusion matrix for Least Squares classification is shown in Table 1.

Table 1: Confusion Matrix for Least Squares Classification

	Predicted Class 1	Predicted Class 2
Actual Class 1	49	1
Actual Class 2	0	50

Fisher Linear Discriminant

The Fisher Linear Discriminant seeks a projection that maximizes the between-class scatter while minimizing the within-class scatter.

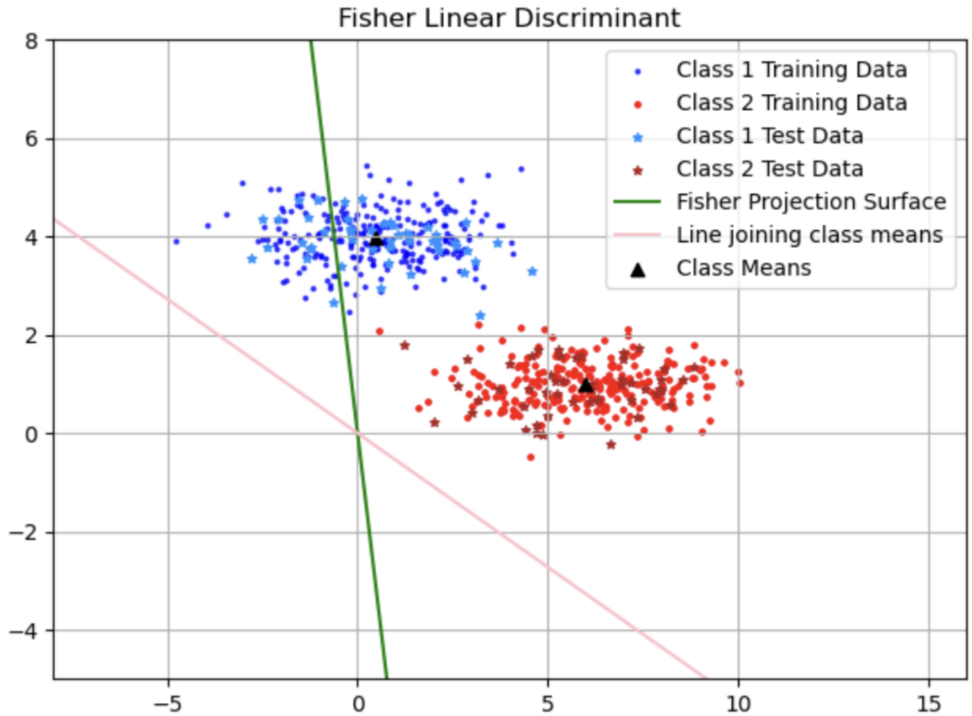

Figure 3: Decision boundary for Fisher Linear Discriminant.

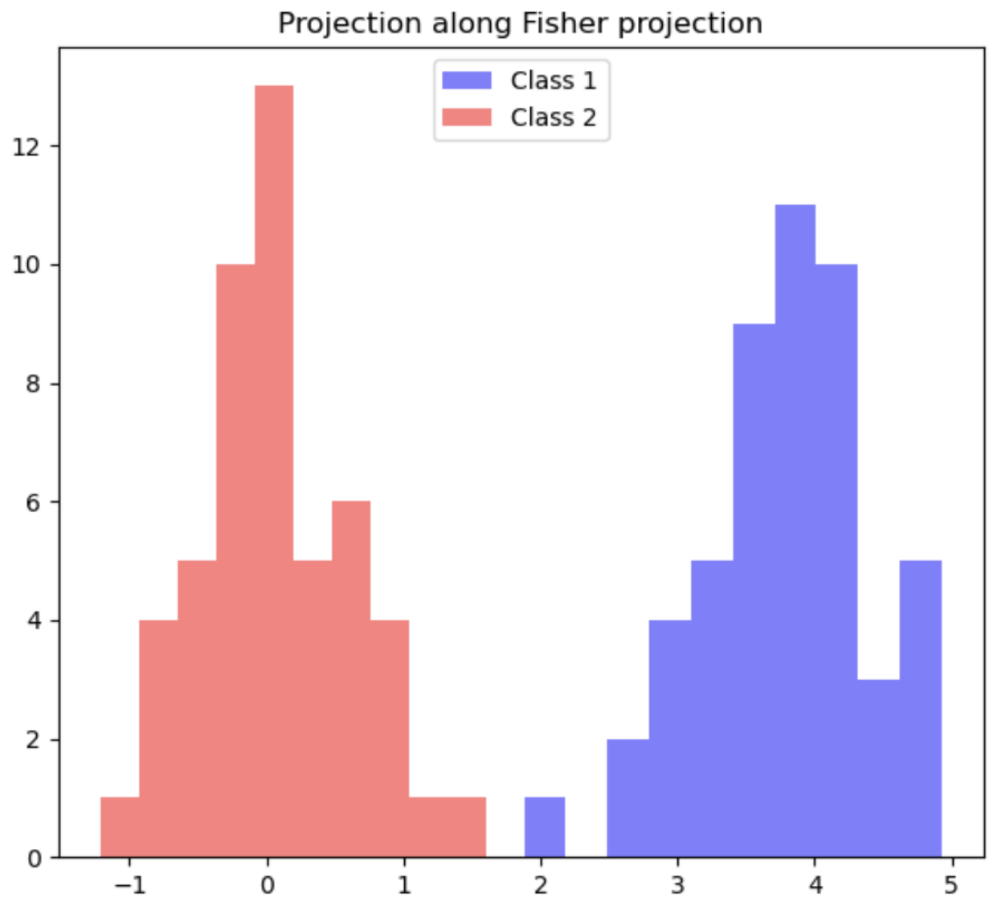

Figure 4: The projection of the two classes onto the line joining the class means.

The confusion matrix for Fisher Linear Discriminant is shown in Table 2.

Table 2: Confusion Matrix for Fisher Linear Discriminant

	Predicted Class 1	Predicted Class 2
Actual Class 1	49	1
Actual Class 2	2	48

Perceptron

The Perceptron algorithm is a learning algorithm that iteratively updates the weights to correctly classify all training examples.

Figure 5: Decision boundary for Perceptron classification.

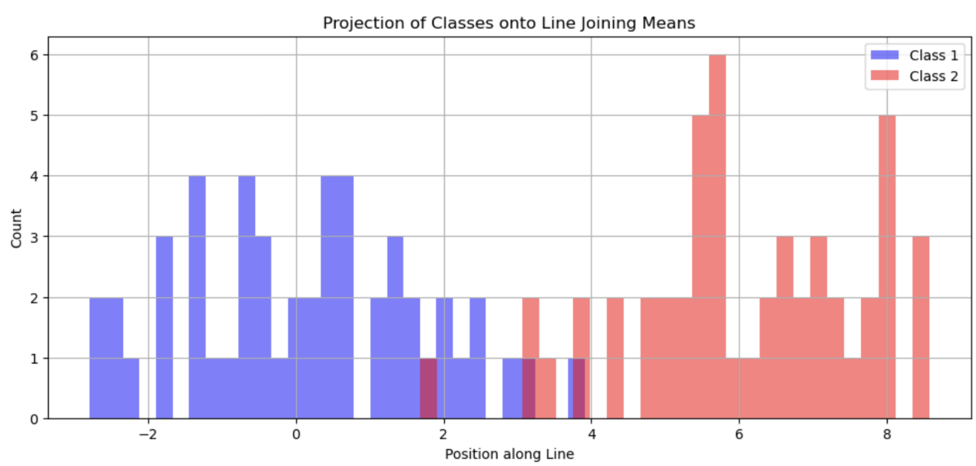

Figure 6: The projection of the two classes onto the line joining the class means.

The confusion matrix for Perceptron is shown in Table 3.

Table 3: Confusion Matrix for Perceptron

	Predicted Class 1	Predicted Class 2
Actual Class 1	49	1
Actual Class 2	2	48

Activity 2

Ridge Regression (Regularized Least Squares)

Ridge Regression implements regularization to the least squares method by adding a penalty term proportional to the square of the magnitude of the coefficients.

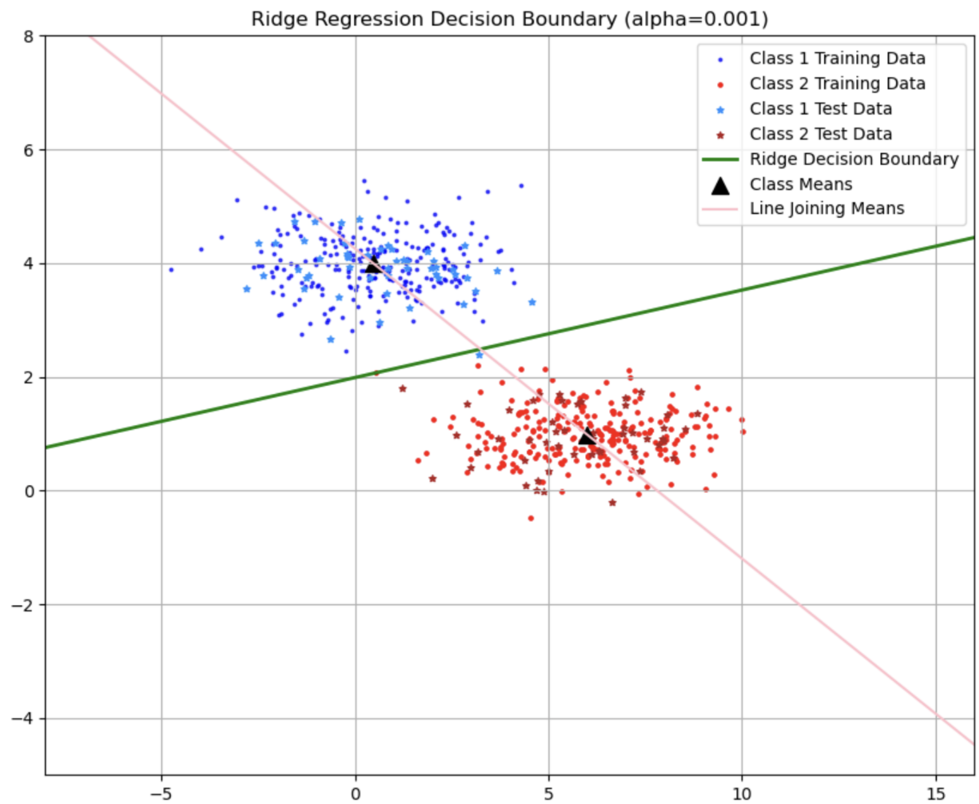

Figure 7: Decision boundary for Ridge Regression with optimal regularization parameter.

Figure 8 shows how the accuracy of Ridge Regression varies with different regularization strengths.

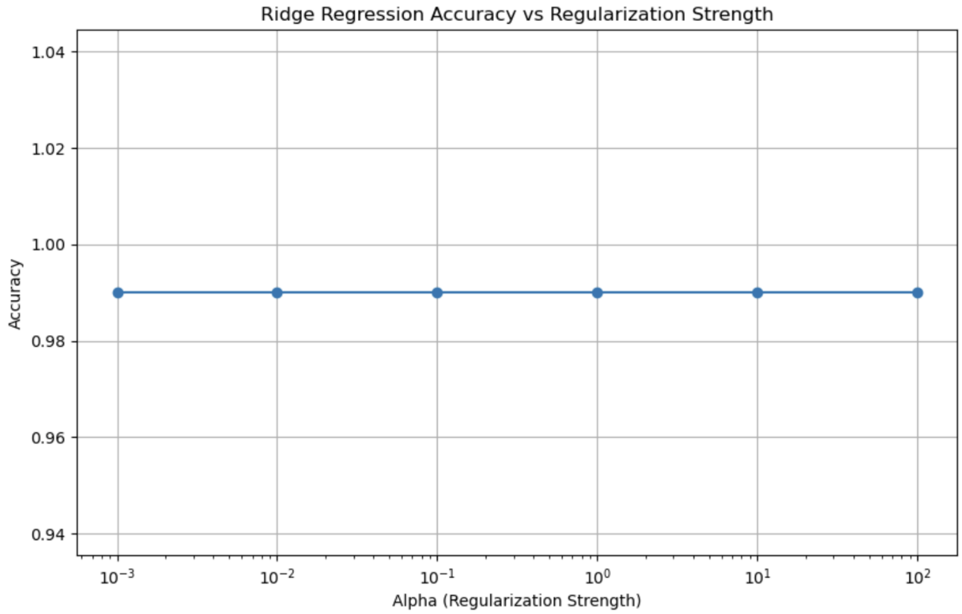

Figure 8: Accuracy vs. regularization strength (alpha) for Ridge Regression.

The confusion matrix for Ridge Regression with optimal regularization parameter is shown in Table 4.

Table 4: Confusion Matrix for Ridge Regression

	Predicted Class 1	Predicted Class 2
Actual Class 1	50	0
Actual Class 2	1	49

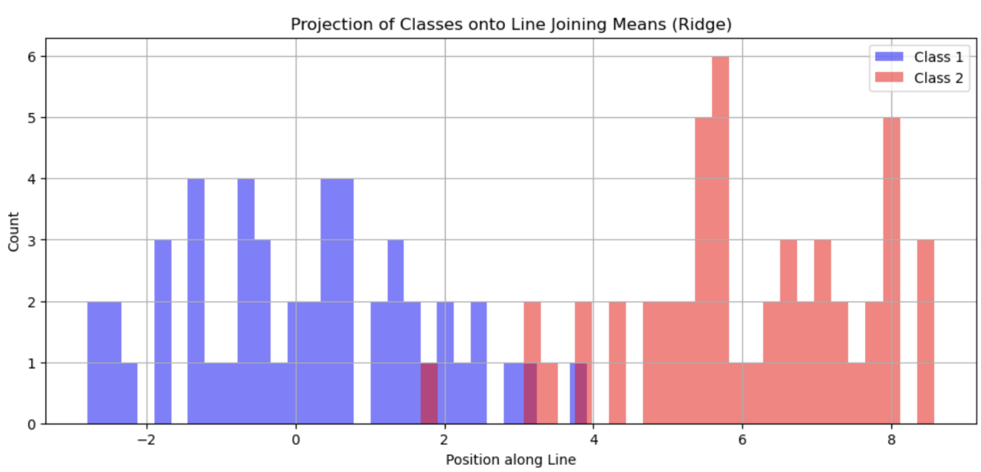

Figure 9: The projection of the two classes onto the line joining the class means.